International Journal of Mechanical and Production
Engineering Research and Development (IJMPERD)
ISSN(P): 2249–6890; ISSN(E): 2249–8001
Vol. 10, Issue 2, Apr 2020, 1409–1418

MANUFACTURING AND SCHEDULE PLANNING VIA BLACK WIDOW OPTIMIZATION ALGORITHM

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ABSTRACT

This study seeks to address problems in manufacturing, and in particular, schedule planning. Black Widow Optimization (BWO) metaheuristic is the algorithm employed , which can identify the optimal usage of the variables in the manufacturing process. Computational experiments are carried out with data provided by an unspecified manufacturer, under varying constraints. The findings indicate that various problems can be solved by BWO with superior efficiency to alternative approaches and within a reasonable timeframe. The findings also suggest that future studies should seek to provide a comprehensive comparison with alternative metaheuristics, and more complex problems should be addressed, such as those involving different product groups or demand patterns.

KEYWORDS: Manufacturing and Scheduling Planning, Yield Optimization, Metaheuristic & Black Widow Optimization

Received: Feb 16, 2020; **Accepted:** Mar 06, 2020; **Published:** Apr 17, 2020; **Paper Id.:** IJMPERDAPR2020133

Original Article

1. INTRODUCTION

There are two basic types of optimization algorithm: approximation optimization algorithms and conventional optimization algorithms. The former can be employed to find the best value for a solution when a conventional optimization algorithm is used. However, while it is effective with small problems, it can be much harder to find a solution in the case of large problems. Notably, where problems are of the NP-Hard type, a slight increase in the size of a problem results in a much longer time, which is necessary to determine a solution. In this scenario, the approximation principle offers the best approach to determine a direct solution. The techniques of this type can be used to solve much larger and more complex problems. The branch of metaheuristics deals with using the approximation principle to discover the optimal solution. It allows complex problems to be processed rapidly, with the traveling salesman problem among the common examples. The different metaheuristic approaches can be separated into four categories. The first type is known as evolutionary algorithms, such as Evolutionary Strategy (ES) (Cheng et al., 2007), and Genetic Algorithm (GA) (Cus and Balic, 2003). Second group is Animal Algorithm. The popular member in this group are Grey Wolf Optimization algorithm (GWO) (Mirjalili et al., 2014), and Artificial Bee Colony (ABC) (Karaboga, 2005). Physical algorithm is a third group. This group includes Simulated Annealing (SA) (Granville et al., 1994), Gravitational Search Algorithm (GSA) (Rashedi et al., 2009), and Thermal Exchange Optimization (TEO) (Kaveh and Dadras, 2017). The last group simulates Human Behavior such as Tabu Search (TS) (Lokketangen et al., 1994) and Teaching-Learning-Base Optimization (TLBO) (Rao et al., 2011). These techniques generate solutions which might not represent the optimal answer, but instead produce a group of answers. The working process continues to operate until the conditions, which were specified from the outset are achieved. Typical examples of this approach include the TEO, and GA which are techniques that involves adjustments whereby different methods can be combined in order to eliminate any shortcomings and find new ways

to reach a solution through a combination of different principles. Each technique will find answers in its own specific way. This research paper describes an approach to discovering optimal solutions. This is known as BWO (Hayyolalam and Kazem, 2020), which is a type of metaheuristic algorithm initially introduced in 2020 by Hayyolalam and Kazem.

2. BLACK WIDOW OPTIMIZATION ALGORITHM (BWO)

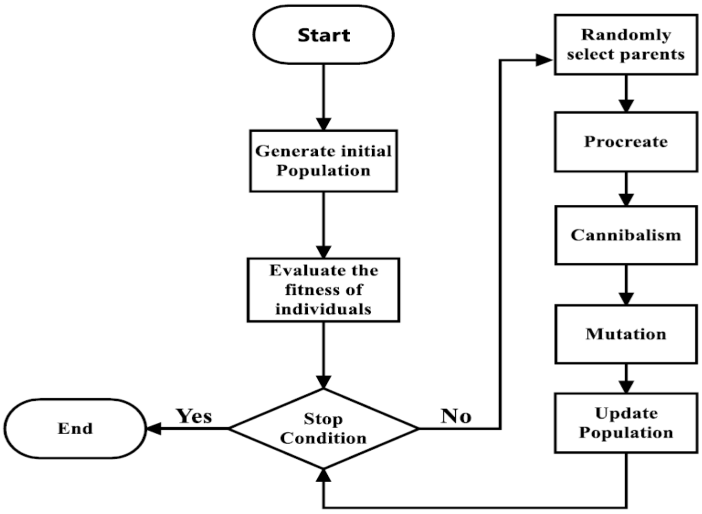

Figure 1: Flowchart of the BWO (Hayyolalam and Kazem, 2020).

The flowchart for the algorithm proposed by this study appears in Figure 1. The algorithm begins with a population of spiders whereby each of the spiders can be understood to represent one possible answer. The spiders then pair up to reproduce, creating a new generation. Female black widows are known to devour the male during mating or upon the conclusion of mating, as can be seen in Figure 2. The female then stores the sperm in her cae before they are allowed to enter the egg sac, as can be observed in Figure 3(a). The baby spiders appear after 11 days, and will live together on the web of the mother spider for up to a week, often eating each other, as shown in Figure 3(b). They eventually leave the web when they are carried away by the wind.

Figure 2: A Female Black Widow Spider in Her Web (Hayyolalam and Kazem, 2020).

(a) **(b)**

Figure 3:(a) A Female Black Widow Spider with the Egg Sac, (b) Baby Spiders Leave Their Egg Sac (Hayyolalam and Kazem, 2020)**.**

2.1 Initial Population

In the context of an N_{var} –dimensional problem of optimization problem, one widow represents an array of 1 × N_{var} which can be seen as a problem solution. The array has the definition given as:

$$\text{Widow} = [x_1, x_2, \ldots, x_{N_{\text{var}}}] \tag{1}$$

Each variable $(x_1, x_2, \ldots, x_{N_{\text{var}}})$ serves as a floating-point number. The widow fitness can be determined by assessing the fitness function f at each widow given as $(x_1, x_2, \ldots, x_{N_{\text{var}}})$. Therefore,

$$\text{Fitness} = f\,(\text{widow}) = f\,(x_1, x_2, \ldots, x_{N_{\text{var}}}), \tag{2}$$

In order for the optimization algorithm to begin, it is necessary for one candidate widow matrix of the size $N_{pop} \times N_{\text{var}}$ to be created with its starting spider population.

2.2 Procreate

In order to achieve reproduction, the algorithm makes use of an array known as alpha, which is developed as the widow array using random numbers, where the resulting offspring are generated through the use of α with the equation given below (Equation 3) where x_1 and x_2 represent the parents while y_1 and y_2 are the offspring.

$$\begin{cases} y_1 = \alpha \times x_1 + (1-\alpha) \times x_2 \\ y_2 = \alpha \times x_2 + (1-\alpha) \times x_1 \end{cases} \tag{3}$$

This process is carried out repeatedly for a total of $N_{\text{var}}/2$ times, although there should be no duplication of numbers selected at random. At the end, the offspring and mother can be added to an array before undergoing sorting on

the basis of their fitness values.

2.3 Cannibalism

There are three different types of cannibalism that occur. Sexual cannibalism arises when the female eats the male either during or after mating. The algorithm is able to distinguish between male and female spiders by considering their fitness values. Sibling cannibalism occurs when stronger baby spiders eat weaker baby spiders. The algorithm applies a Cannibalism Rating, or CR, which sets the number of spiders which will survive. It is also possible for baby spiders to eat the mother spider. The algorithm uses the fitness value to establish whether baby spiders are weak or strong.

2.4 Mutation

At this point, the random selection of Mutepop number of individuals from the population takes place. The solutions chosen will randomly have two of their elements from the array rearranged, as Figure 4 shows. In order to calculate Mutepop, the mutation rate is used.

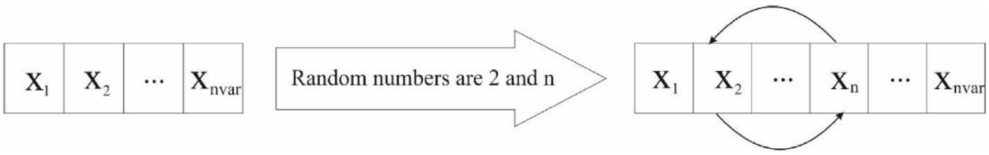

Figure 4: Mutation [15].

2.5 Convergence

As would be the case for other evolutionary algorithms, there are three stop conditions which can be applied: (a) a predefined number of iterations. (B) Observance of no change in the fitness value of the best widow for several iterations. (C) Reaching to the specified level of accuracy.

2.6 Parameter Setting

In the BWO algorithm under examination, certain parameters are required in order to achieve improved results. These particular parameters are the procreating rate (PP), cannibalism rate (CR), and mutation rate (PM). The values selected in this research for these particular parameters can be seen in Table 1.

Table 1: The Set Parameter Values

Parameter	Value
PP = procreate rate	0.70
CR = cannibalism rate	0.45
PM = mutation rate	0.60

3. MANUFACTURING MODEL

3.1 Manufacturing Model 1

Model 1 allows the analysis of an experimental design in order to determine the influence of the cutting parameters including feed rate, cutting speed and depth of cut on surface roughness in turning process (Pansare and Kavade, 2012). The model below was proposed by:

$$Ra = 8.11 - 0.0217A - 25.9B - 6.37C + 0.0563AB + 0.0153AD + 19.4BC \tag{4}$$

where A is the cutting speed (m/min), B is the feed rate (mm/rev), C is the depth of cut (mm), and Ra is the

surface roughness (µm). The formulation of the turning optimization problem takes place as shown below:

$$Minimize\ R_a = f(A,B,C)$$

Subject to:

$$150 \le A \le 250 \text{ (m/min)}; 0.1 \le B \le 0.2 \text{ (mm/rev)}; 0.5 \le C \le 1.5 \text{ (mm)} \quad (5)$$

3.2 Manufacturing Model 2

The objective of the next model is to discover the optimal values for the parameters in turning operations to maximize the MRR (Material Removal Rate) (Shivakoti et al., 2012). To calculate MRR, the following regression equation was developed:

$$MRR = 1.42 - 1.83A - 0.9B + 10C + 103AB - 112AC + 0.000014BC \quad (6)$$

where A is the feed rate (mm/rev), B is the spindle speed (rpm), and C is the cutting speed (m/min). Equation 7 was chosen as the objective function via formulation of the optimization problem to determine the most suitable cutting parameters as follows:

$$Maximize\ MRR = f(A,B,C)$$

Subject to:

$$0.62 \le A \le 0.98 \text{ (mm/rev)}; 40 \le B \le 1000 \text{ (rpm)}; 3.5 \le C \le 95.5 \text{ (m/min)} \quad (7)$$

3.3 Manufacturing Model 3

The goal is to apply the regression equations in order to generate mathematical models (Saravanakumar et al., 2012) of the Material Removal Rate (MRR) and surface roughness Ra in the following:

$$MRR = 19158 - 298A - 112136B + 91493C + 1749AB + 1417AC + 537343BC - 7880ABC \quad (8)$$

$$R = 23.6 - 0.331A - 110B - 88C + 166AB + 1.29AC + 463BC - 6.93ABC \quad (9)$$

where A is the cutting speed (m/min), B is the feed rate (mm/rev), and C is the depth of cut (mm). To identify optimal cutting parameters, Equation 8 must be maximized while Equation 9 must be minimized with regard to the machining parameter constraints given as:

$$60 \le A \le 80 \text{ (m/min)}; 0.15 \le B \le 0.25 \text{ (mm/rev)}; 0.1 \le C \le 0.25 \text{ (mm)} \quad (10)$$

3.4 Manufacturing Model 4

In this problem, there were five machines and 20 products. Table 2 shows the time taken for the processing of each product. The precise solutions or product sequences in this problem are shown as follows:

Table 2: Product Processing Time for Each Machine for the Manufacturing Model

Product	Processing Time t_{ij} (mins)Machine					Due Time d_i (mins)	Penalty p_i ($/min)
	1	2	3	4	5		
A	62	77	65	79	81	850	55.00

B	47	44	84	50	67	1,210	35.00
C	97	77	99	33	26	350	15.00
D	87	2	88	7	91	575	90.00
E	38	62	95	43	15	810	100.00
F	67	10	86	11	39	1,060	90.00
G	31	8	69	61	7	475	30.00
H	24	64	30	41	25	655	30.00
I	72	37	84	66	14	555	25.00
J	37	77	60	75	82	1,100	80.00
K	47	80	91	6	17	890	80.00
L	49	86	6	89	92	1,055	45.00
M	25	5	8	42	6	815	85.00
N	48	8	55	82	7	700	40.00
O	97	76	54	64	66	1,205	40.00
P	16	27	11	5	64	910	70.00
Q	43	69	61	6	85	360	75.00
R	41	5	28	32	38	715	90.00
S	44	26	7	19	40	480	60.00
T	10	37	23	29	100	850	15.00

4. RESULTS AND DISCUSSIONS

For the purposes of this study, BWO was written using a MATLAB 2019, a computer program and the computational experiments were conducted using HP laptop. Assessments were then made of the BWO, TEO, and GA so as to compare the overall performance. For each algorithm, the main parameters have their own influence over performance in achieving the optimal quality of solution or shortest computational time. The best parameter choices for the problems are determined by considering previous experiments, with each algorithm using values suggested in the literature. Development of the parameter values was accomplished through the experimental designs, whereupon the findings were investigated to determine the quality of the solutions. For the final BWO algorithm, the parameters were set in the form, as shown in Table 2. Each of the algorithms then underwent execution using the maximum evaluation number up to 10,000, and for each problem, the algorithm performed 30 repetitions.

The performance of a number of different metaheuristics is listed in Tables 3, 4, and 5, in the context of roughness minimization, maximization of the material removal rate, and optimization problems with various constraints and limitations. The study takes into consideration four separate measures of performance for comparison purposes. These include the average, maximum, minimum, and standard deviation for both the execution time and the yield. The BWO was shown to be capable of approaching the optimal point with superior performance to the alternatives. One of the key strengths of BWO is its efficiency of computation, as shown in Figure 6. In the case of an earlier optimization setting, all of the tested metaheuristics were capable of delivering results close to the optimum. For most of the techniques, the standard deviation is very small, but in the case of BWO, it is very near to zero. In the case of GA, the time taken for computation is lower than for all the alternatives.

Table 3: Experimental Result on the Manufacturing Model 1

Model 1	BWO		TEO		GA	
	Yield	Time	Yield	Time	Yield	Time
Average	0.036	69.9	0.085	70.6	0.06	69.8
Std. Dev.	0.004	1.25	0.05	1.13	0.08	1.01
Max	0.038	71.87	0.102	71.89	0.12	71.84
Min	0.032	68.42	0.039	68.38	0.04	68.56

Table 4: Experimental Result on the Manufacturing Model 2

Model 2	BWO		TEO		GA	
	Yield	Time	Yield	Time	Yield	Time
Average	99,668	65.5	99,651	66.0	99,656	60.7
Std. Dev.	23.7	1.0	41.43	1.0	40.02	0.9
Max	99,686	67.5	99,685	67.6	99,685	63.4
Min	99,651	64.0	99,628	64.3	99,628	58.2

Table 5: Experimental Result on the Manufacturing Model 3

Model 3	BWO		TEO		GA	
	Yield	Time	Yield	Time	Yield	Time
Average	2,003	66.0	2,028	66.1	2,024	60.7
Std. Dev.	88.5	1.04	72.7	1.15	96.7	1.02
Max	2,066	67.5	2,080	68.0	2,093	63.2
Min	1,940	64.4	1,977	64.3	1,956	58.2

This was a bigger and more complex problem. In considering the details of the five machines and 20 products in a given factory, it is apparent that BWO offers the smallest penalty at US $104,020, while the order of production is [L J Q E F N P D A R C M H T K G I B O S]. The next and final approaches are GA and TEO, which offer the next smallest penalty values at US $107,480 for GA and US $110,365 for TEO. These results can be observed in Table 6.

Table 6: The Findings for the Minimum Make Span in the Scheduling Problem

Methods	Sequences	Minimum make span (US$)
BWO	[L J Q E F N P D A R C M H T K G I B O S]	104,020
TEO	[J Q L E F P N C T D A R H M K G I B O S]	110,365
GA	[J Q L E T F P N D A R C H M K G I B O S]	107,480

The results of the statistical analysis of the performance of BWO and the alternative algorithms, GA and TEO, can be seen in Table 7. The table shows that BWO has a better mean value than the alternatives, but the robustness of TEO was shown to be superior to BWO, as indicated by the standard deviation (Std. Dev.). The CPU times which are given in seconds do not show any major differences between the three approaches.

Table 7: A Comparison of the Data Analysis Findings for the Different Algorithms Addressing the Scheduling Problem

Methods	Mean	Best	Worst	Std. Dev.	CPU. time (s)
BWO	104,320	104,020	104,595	420.2	74.9
TEO	110,314	110,365	110,410	28.4	87.6
GA	107,951	107,480	108,435	675.2	76.0

It is necessary to start with a fixed fitness constraint, if the three methods are to be applied and tested fairly in order to present the correlation between the objective function value and the number of iterations. Figure 5 presents the rate of convergence at population size set of 50. The data show that GA offers much faster rates of convergence than the alternative approaches, with the drawback that the GA solution is unable to move beyond the local optimum when attempting to solve the scheduling problem. The BWO algorithm provides a slower convergence rate than the GA algorithm, but does reach a global optimum. Furthermore, the answer generated after testing with the number of evaluations set at 10,000 revealed that the BWO approach was superior to the two alternatives.

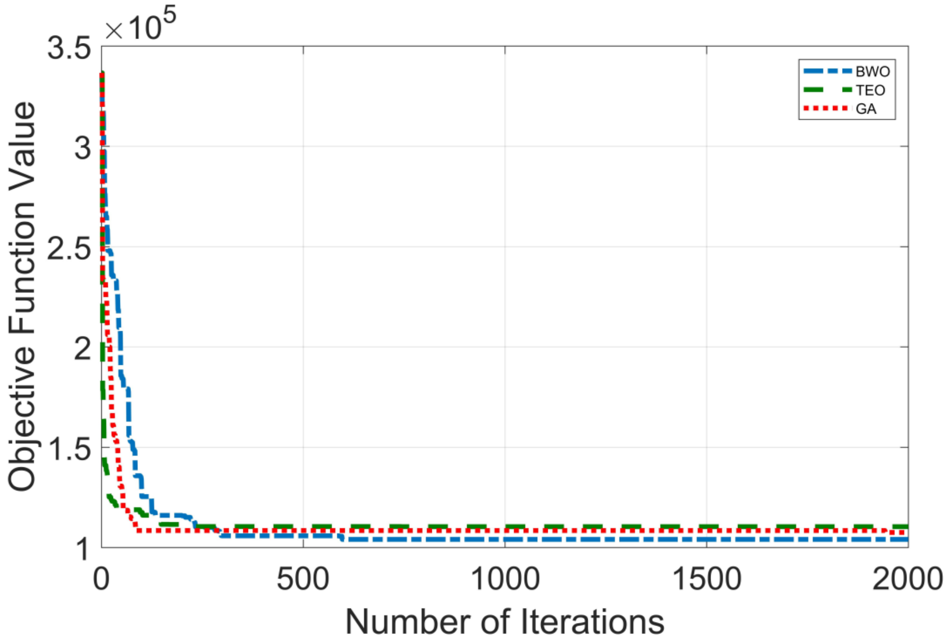

Figure 5: Comparison of Convergence Rates for the Pressure Scheduling Problem.

5. CONCLUSIONS

This research study assesses the effectiveness of the novel BWO metaheuristic algorithm through testing in the context of different manufacturing problems where both maximization and minimization methods are used, in addition to solving scheduling problems. The data reveal that BWO is able to compete effectively with other approaches, and delivers a higher degree of accuracy than the alternatives. The GA produced the best performance in the context of computational effort, although the yields were not as good as others. The findings in this study suggest that future work should involve a more complete comparison with the alternative metaheuristics, and more complex problems should be addressed, such as product groups and differing demand patterns. Moreover, it is known that further research into parameter values usually lead to enhanced solutions when the final generation to the optimal solution vector is reached.

ACKNOWLEDGEMENTS

The authors of this paper gratefully acknowledge the financial support of the Department of Mechatronics and Robotics Engineering, Faculty of Technical Education, Rajamangala University of Technology Thanyaburi.

REFERENCES

1. *Cheng, Y. M., L. Li & Chi S. C. (2007). Performance Studies on SiHeuristic Global Optimisation Methods in the Location of Critical Slip Surface Computers and Geotechnics. Computers and Geotechnics, 34, 462– 484*
2. *Cus, F., & Balic, J. (2003). Optimisation of Cutting Process by GA Approach. Robot. and Com. Integ. Manu, 19, 113–121*
3. *Granville, V., Krivanek, M., &Rasson, J. P. (1994). Simulated annealing: a Proof of Convergence. Pattern Analysis and Machine Intelligence, IEEE Transactions, 16(6), 652–656*
4. *Kaveh, A.&Dadras A. (2017). A novel meta-heuristic optimization algorithm: Thermal exchange optimization. Adv. Eng. Softw., 110, 69–84*
5. *Mirjalili, S. A. & Mirjalili, S. M., & Lewis, A. (2014). Grey wolf optimizer. Adv. Eng. Softw., 69, 46–61*

6. Pansare, V. B., & Kavade, M. V. (2012). Optimization of cutting parameters in multipass turning operation using ant colony algorithm. International Journal of Engineering Science & Advanced Technology, 2(4), 955–960
7. Rao, R. V., Savsani, V. J., & Vakharia, D. P. (2011). Teaching – learning - based optimization: a novel method for constrained mechanical design optimization problems. Comput. Aided Des, 43(3), 303–315
8. Rashedi, E., Nezamabadi-pour H., &Saryazdi, S. (2009). A gravitational search algorithm. Inf. Sci., 179, 2232–2248
9. Saravanakumar, K., Shaik, A. K. D., & Kumar, M. R. (2012). Optimization of CNC Turning Process Parameters on INCONEL 718 Using Genetic Algorithm, Engineering Science and Technology: An International Journal, 2(4), 532–537
10. Shivakoti, I., Diyaley, S., Kibria, G.,& Pradhan, B. B.(2012). Analysis of Material Removal Rate using Genetic Algorithm Approach, International Journal of Scientific & Engineering Research, 3(5), 1–6
11. " An Efficient Modified Cuckoo Search Optimization with the Rational Barrier Function ", International Journal of Mathematics and Computer Applications Research (IJMCAR), Vol. 8, Issue 5, pp. 13-24
12. " An Appraisal of Issues Faced by Manufacturing Companies when Selecting 3 an Enterprise Resource Planning (ERP) System ", International Journal of Business and General Management (IJBGM), Vol. 7, Issue 1, pp.1-8

    " A Case Study on Occupational Health and Safety of Footwear Manufacturing Industry ", IASET: Journal of Business and General Management (IASET: JBGM), Vol. 2, Issue 1, pp. 1-6